Leveraging Remote Diagnostics Data for Predictive Maintenance

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Abstract

Embedded sensors are used in many applications to collect remote diagnostics data, providing valuable information about the health of a system during its operation. In addition to detecting problems that need immediate attention, this information can be used in conjunction with historical reliability data to determine how the system is aging or degrading over time. This presentation will describe approaches for analyzing remote diagnostics data for the purpose of predictive reliability, durability, and maintenance. Examples from GE's businesses, including aircraft engines, will illustrate the value of these techniques in practice.

Introduction

One of the most important advances in the area of predictive maintenance involves the use of embedded sensors in complex systems to collect remote diagnostics data. This data provides a snapshot of the health of the system during its operation. An aircraft engine provides an excellent example of such a system where various temperatures (intake, exhaust gas, etc.), pressures, and operating condition data (thrust, dust concentration, etc.) are available at both take-off and cruise conditions. This data has proved to be valuable not only in detecting problems that need immediate attention, but also when used in conjunction with historical reliability data to determine how the system is aging or degrading over time.

One challenge in utilizing such data for reliability analysis lies in the development of the proper mathematical framework to "piece together" information from each use of each system in the study (e.g., each flight of each of the aircraft engines in a fleet) in order to properly account for the aging that is taking place over time. Clearly, if each system in a study operates under one set of conditions throughout its life, the analysis is greatly simplified. Lifetime regression methods like Weibull regression (Lawless, 1982 and Meeker, 1998) can be used to account for the various operational environments and determine the relative importance of various remote diagnostic parameters on predicting reliability. Unfortunately, however, the problem is usually complicated by the fact that every use of an engine may be different. For example, during one flight the engine may be operated at full thrust at take-off with an ambient temperature of 75 degrees, and during the next flight may be operated at 50% of full thrust with an ambient temperature of 34 degrees. Physics based models and experience suggest that the wear experienced by the engine under these flights are different, and therefore neither hours of operation nor number of cycles (i.e., number of take-offs) can fully account for the total aging of the engine from a reliability perspective.

Accounting for the accumulation of wear

In order to perform this accounting for wear, we extend a technique of accumulating damaged in accelerated testing studies presented by Nelson (2001). In our formulation the cumulative hazard function is utilized as the true metric for age of the system. By translating between the time domain (e.g., cycles or hours) and the cumulative hazard domain, one is able to develop a methodology for accumulating the wear that occurs during each use of the system thereby providing improved predictability of reliability of the overall system.

As a simple example, consider a system A which operates under one set of conditions (stress level 1) from time 0 until t_1 and then operates under a different set of conditions (stress level 2) from time t_1 until t_2. At time t2 we wish to compare the age of a part installed in system A to one installed in another system B which operates under the second set of conditions (stress level 2) from the total time 0 until t_2. To simplify the analysis, assume that the part's reliability follows a Weibull distribution and (η_1, β_1) represent the scale and shape parameters associated with stress level 1 and (η_2, β_2) are the scale and shape parameters associated with stress level 2. Then, at time t_1, the part in system A has cumulative hazard: $H_A(t_1) = \left(t_1 / \eta_1 \right)^{\beta_1}$

In order to find the time, s, at stress level 2 that corresponds to this level of wear, we solve:

$\left(t_1 / \eta_1 \right)^{\beta_1} = \left(s / \eta_2 \right)^{\beta_2}$ for s and obtain: $s = \eta_2 \left(t_1 / \eta_1 \right)^{\beta_1 / \beta_2}$

We can therefore calculate the cumulative hazard for the part in system A at time t_2 by:

$$H_A(t_2) = H_A(t_1) + \int_s^{s+(t_2-t_1)} \left(\frac{x}{\eta_2} \right)^{\beta_2 - 1} \frac{\beta_2}{\eta_2} dx = \left[\left(\frac{t_1}{\eta_1} \right)^{\beta_1/\beta_2} + \frac{t_2 - t_1}{\eta_2} \right]^{\beta_2}$$

In terms of units of time under stress level 2, this is equivalent to:

$$t = \eta_2 \left[H_A(t_2) \right]^{1/\beta_2} = \eta_2 \left(\frac{t_1}{\eta_1} \right)^{\beta_1/\beta_2} + t_2 - t_1$$

and, if stress level 2 is assumed to be more stressful than stress level 1, we can conclude that the part in system B is $t_1 - \eta_2 \left(\frac{t_1}{\eta_1} \right)^{\beta_1/\beta_2}$ time units older (in terms of stress level 2) than the part in system A.

Formulating a life regression model

Armed with the above methodology of accounting for accumulated damage over time, we can extend traditional failure time regression analysis models to determine the relative importance of various engine operational factors by forming the corresponding likelihood functions and using MLE to estimate the parameters. This process is simplified by the fact that:

$$f(t) = -\frac{d}{dt}\exp(H(t))$$

enabling us to relate the above formulation directly to the probability density function. For example, consider a part installed in an engine and assume a proportional hazard Weibull model (Lawless, 1982) with constant shape parameter β and scale parameter in the form:

$$\eta_j = \exp\left\lfloor \alpha_{j,0} + \alpha_{j,1}x_{j,1} + \alpha_{j,2}x_{j,2} + \ldots + \alpha_{j,K}x_{j,K} \right\rfloor$$

where x_{jk} represents the value of the output of the k^{th} sensor during the j^{th} flight and α_{jk} are the corresponding regression parameters. Then if N is the number of parts in our sample (one part per engine), N_1 the number of parts that have failed, m_i the number of flights by engine i, and t_j is the time at the end of the jth flight, then the log likelihood function is given by:

$$L_N = -\sum_{i=1}^{N}\left[\sum_{j=1}^{m_i}\frac{t_j - t_{j-1}}{\eta_j}\right]^{\beta} + (\beta - 1)\times\sum_{i=1}^{N_1}\ln\left(t_{m_i} - t_{m_i - 1}\right) - \beta\times\sum_{i=1}^{N_1}\ln\left(\eta_{m_i}\right) + N_1\ln(\beta)$$

Application to the predictive maintenance

An interesting application of these analytical techniques is in maximizing the life of repairable parts in an aircraft engine. At each engine shop visit, these parts are removed from the engine and examined to determine if they need to be repaired or replaced. Repaired parts are placed into an inventory pool to be installed on another engine entering the shop at a later date. The objective is to always replace the part long before it would pose a reliability problem (i.e., force an engine shop visit), but repair the part as many times as feasible in order to minimize costs. For many such parts, the cost of repair is only one tenth of the cost of replacement.

In order to develop an optimal strategy for maximizing part life and minimizing cost, the technique described in the previous section is used to estimate each part's effective age based on its historical usage. Then, by utilizing a dynamic programming model, the best set of parts from the inventory can be chosen to populate a particular engine entering the shop in order to maximize overall part life based on the projected future operation conditions of that engine. Simulation studies comparing random part usage vs. this optimal procedure on actual data demonstrates such a technique has a substantial impact on cost savings.

References

Lawless, J. (1982). Statistical Models and Methods for Lifetime Data. New York: Wiley.

Meeker, W and Escobar, L. (1998). Statistical Methods for Reliability Data. New York: Wiley.

Nelson, W. (2001). Prediction of Field Reliability of Units Each under Differing Dynamic Stresses, from Accelerated Test Data. In N. Balakrishnan and C. R. Rao (Eds.), *Handbook of Statistics, Vol 20,* pp. 611-621. Elsevier Science B.V.